ISSN 2320-9984

Volume 7 Issue 3 | September 2019

ISSN: 2320-9984 (Online)

International Journal of Modern Engineering & Management Research

Website: www.ijmemr.org

Predicting Mental Health Disorders Using CapsFCN and Clinical Assessment Data in the Cloud

Nazmina Dhanji
National Ribat University
Khartoum, Sudan
Email: dhanjinazmina@gmail.com

Abstract**—***Mental health is marked by disturbances such as depression, anxiety disorder, and schizophrenia, creating profound personal, societal, and economic difficulties for millions of individuals across the globe. Traditionally, these disorders were clinically assessed, a process that carries with it a significant element of subjectivity and is sometimes prone to error. The study suggests a hybrid deep-learning model named CapsFCN, which combines Capsule Networks (CapsNet) with Fully Connected Neural Networks (FCNN)-to predict mental health disorders on the bases of symptom data. The purpose is to be able to blend the impact of symptoms with disorders in such a way as to reflect the exacting capability of capturing spatial hierarchies given by CapsNet and the non-linear learning capabilities attributed to FCNN. To make the model available in a more accessible and scalable way, we propose that the application be integrated into the cloud, thus allowing every healthcare professional access to the tool and its utilization for the predictions. The proposed model is validated using standard performance metrics against any existing diagnostic model. With the automation of the prediction process, the model provides an objective means for mental health diagnoses, which is likely to improve patient outcomes by allowing for early interventions.*

Keywords:**—***Healthcare, Capsule Networks, Fully Connected Neural Networks, Deep Learning, Symptom Prediction, Cloud Computing*

1. INTRODUCTION

Mental health disorders like depression, anxiety, and schizophrenia are prevalent around the world, affecting the lives of millions, with attendant personal, societal, and economic implications. These disorders are identified and diagnosed early to facilitate effective treatment and prevention [1]. Diagnosis methods usually entail subjective appraisal by health professionals, which is influenced by personal bias, experience, or intricacies in symptoms. There seems to be a growing need for such automated objective systems which can help in diagnosing mental health disorders [2]. Mamidala and Balachander (2018) developed a DRL-based framework for intelligent cloud resource management, improving efficiency, energy use, and latency. Their work inspires adaptive, cloud-based deployment of mental health prediction models using orchestration and workload-aware decision-making [3].

The advent of new and recent developments in artificial intelligence (AI) and machine learning (ML) offers possibilities to enhance diagnosis of mental health disorders for future applications. Machine learning models, particularly deep learning models, are promising in identifying complex large datasets and as such provide much scope for predicting mental health disorders [4]. With AI, those models will analyse clinical data coupled with symptoms, behavioural patterns, and medical history to come out with prognosis into the individual's mental health condition. However, building models capable of dealing well with symptom data that is richly complex, high dimensional, and frequently sparse, is not without problems [5].

The present work tries to study the feasibility of an approach in which Capsule Networks (CapsNet) are merged with Fully Connected Neural Networks (FCNN) to result in the hybrid model, CapsFCN, for prediction on mental health disorders based on symptom data. Making complex relationships that exist between symptoms and disorders is the focus of the CapsFCN model to predict more accurately [6]. Such applications are, therefore, very much apt to employ Capsule Networks, which retain spatial hierarchies and relationships between features because interactions among symptoms and disorders are important. The Fully Connected Neural Network also helps in capturing certain non-linear relationships that traditional models might have an issue with. It plans to develop a comprehensive and accurate tool in predicting mental health disorders through hybrid innovation [7]. The model can be deployed into the cloud platform that can scale to enable healthcare practitioners to access it. Cloud systems promise to deal with large volumes of data, privacy, and access to the prediction, thus increasing the productivity of the CapsFCN model within the clinical setting [8].

With the cloud infrastructure, this model will keep continuously updating itself so that new data may improve the model's accuracy and adaptability. This AI, deep learning, and cloud nexus is promising in advancing automation in the reliable prediction of mental health care [9]. The intent of this research is to validate the efficacy of the CapsFCN model towards predicting mental health disorders, and to assess the performance of the model with regards to accuracy and reliability. The model will then be subjected to rigorous performance measures to assess its efficacy in the diagnosis disorders-on-symptom-data basis. The model will also be compared with other existing models to evaluate its performance in aspects of accuracy, precision, recall, and F1-score. Nagarajan and Kurunthachalam (2018) optimized cloud-based mental health prediction using CapsFCN, data preprocessing, and compression, achieving 80% latency reduction. Their work informs the novel method by motivating efficient, scalable cloud pipelines for real-time, large-scale healthcare data processing [10].The methodology proposed will start from data collection and preprocessing through feature extraction and classification for final prediction of mental health disorders. By providing research in areas of mental health disorders such as depression and anxiety, this research aims to broaden the scope of AI-based solutions in health care. This is ultimately useful in providing healthcare professionals with the tools that improve their accuracy and timeliness in diagnoses and thus a better outcome to patients.

Problem Statement

Traditional clinical methods are subjective, leading to difficulties in arriving at accurate and timely diagnoses of mental health problems. Symptoms are assessed clinically, further guided by the clinician's opinions or judgments, permitting, thereby, the risk of misdiagnosis and consequent treatable delays that could hinder a better prognosis for the patient [11]. This provides an opportunity for artificial intelligence to facilitate a more objective and coherent approach in predicting mental health disorders based on a consideration of symptoms through machine-learning paradigms, particularly deep learning [12].

This has its own limitations, with a difficulty in correlating the vast complex interactions between symptoms and mental health disorders with the existing models [13].

This paper takes a shot at addressing the various challenges by proposing a hybrid deep learning model named CapsFCN that is an integrated combination of Capsule Networks and Fully Connected Neural Networks for the accurate prediction of mental health disorders based on symptoms. The purpose of such a model is to achieve better prediction accuracy, scalability, and accessibility while using cloud computing with a view to enhancing performance and its deployment in real clinical settings.

Objective

- Understanding the current challenges related to the traditional methods in clinical diagnosis of mental health disorders.
- Investigating how far machine learning models such as CapsFCN show promise for better prediction of mental health disorders from symptoms.
- A hybrid deep learning model is proposed through the combination of Capsule Networks and Fully Connected Neural Networks to capture the complex relationship between symptoms and disorders.
- Evaluate the performance of the proposed CapsFCN model in terms of known performance metrics such as accuracy, precision, recall, and F1 score.
- Cloud computing integration should be enhanced in order for the model to be accessed, scalable, and flexible for applications in real clinical practice.
- Comparison of the CapsFCN model performance against existing diagnostic models to produce its effectiveness, reliability, and necessary argumentation data to improve the clinical decision-making for mental health care.

2. LITERATURE SURVEY

In recent years, predicting mental health disorders through using advanced machine learning techniques has gained much recognition among many studies, demonstrating how well they could help with early detection and improving the accuracy of diagnosis [14]. Traditional methods of diagnosis for mental health disorders have relied on clinical assessments or subjective judgment by health care providers, thus giving rise to various misdiagnoses and delays in treatment. Machine learning models, on the other hand, can process hundreds of thousands of pattern symptoms, medical histories, and demographics for correlation and prediction purposes against various possible conditions of mental health [15].

It promotes a far more objective and uniform way of reducing human error, thus enabling reliable diagnoses. Various algorithms such as decision trees, SVM, neural networks, and even some deep learning techniques have been explored for this purpose in the years to date [16]. Particularly, deep learning techniques provide a very powerful approach to predicting mental health, as they have the capability of learning complex, nonlinear relationships in high dimensional data.

The use of Capsules Network (CapsNet), introduced by Geoffrey Hinton and colleagues, is becoming the latest neural architecture for deep learning to represent constituent relations and, at the same time, preserve spatial hierarchies in making a feature extraction. The intended strategy applies quantum-resistant encryption to protect sensitive clinical mental health data in resource-constrained cloud environments, enthused by Gudivaka and Rathna's (2018) [17] proposal of using Frodo KEM post-quantum encryption to secure IoT-cloud data efficiently. While these characteristics have made these networks very relevant for problem-solving tasks where it involves understanding relationships between parts of data, symptoms becoming critical in a correct classification. The ability of CapsNet to maintain spatial and hierarchical relationships is an advantage, particularly when the interactions between symptoms and disorders might not be linear or straightforward, as in the case of predicting mental health problems.

There have been successful applications of Capsule Networks in image recognition and natural language processing, and interest has now developed around their use for applications in health care, including prediction of mental health disorders [18]. Nonetheless, the application of CapsNet for mental health disorders is not well explored, leaving a huge gap for research in this area.Fully Connected Neural Networks (FCNNs) have been extensively deployed for classification tasks including various mental health classifications. Using FCNNs, complex, non-linear relations can be learnt between features through complete connection of neurons in one layer with all other neurons in the subsequent layer [19].

They proved to be effective especially when working with large quantities of data that need learning of high-level abstractions. By hybridization of Capsule Networks with Fully Connected Networks in such a form that it is called CapsFCN, both the types of networks can be integrated to take advantage of both strains. This makes CapsNet able to generate models for complex part-whole relations and, at the same time, FCNN works perfectly for learning non-linear patterns in high-dimensional data. Very promising results can be obtained in the prediction of mental health disorders uses their symptoms on this hybrid model. Such a hybrid model would improve the prediction by extracting both finer details and more abstract features from such data [20].

Considering all the above factors, we can say that cloud computing has become a primary enabler in modern AI applications such as healthcare, where datasets can be very large and computational resources can be costly and very hard to manage locally [21]. By deploying machine learning models on the cloud, the researchers and health care practitioners guarantee that the model is scalable, accessible, and easy to use. They provide platforms that allow sensitive data to be stored in compliance with privacy regulations, which is a significant concern when dealing with critical applications such as those in health care. Also, cloud integration enables the the updating of models, ensuring that the predictions remain accurate and relevant as new data pour into the cloud. There have been many studies on the successful implementation of cloud computing in health care, especially in medical imaging and patient monitoring [22].

The combination of machine learning, cloud computing, and deep learning for predicting mental disorders is one of the promising approaches in the future of healthcare. Chetlapalli and Bharathidasan (2018) [23] developed a cloud-based, explainable AI framework for brain tumor detection using EfficientNet and SHAP. Their approach encourages this work's emphasis on combining deep learning, interpretability, and scalable cloud deployment for mental health disorder prediction. Automated diagnosis systems based on AI can relieve many healthcare professionals from nonessential duties that would enable these professionals to focus on the personalized care and treatment plans. Similarly, such diagnosis systems provide a rapid and reliable diagnosis, which results in the early treatment of patients and improvement in patient outcomes.

3. PROPOSED METHODOLOGY

Figure 1 displays the process of diagnosing mental health disorders using the CapsFCN model, beginning with data collection-where data on symptoms and disorders are collected. Thereafter, a series of preprocessing steps are undertaken upon data cleaning, wherein the symptoms coded, structured, and organized into data that were ultimately suitable for a machine. This was followed by feature extraction, which applies binary encoding to convert symptoms for the model in a usable format [24].The model is then put into classification using the CapsFCN in which the Capsule Network and Fully Connected Neural Network serve in combination to predict mental health disorders. After that, cloud integration allows model deployment for scaling uses. Finally, the performance of the model gets assessed through performance metrics to evaluate the model's accuracy and effectiveness in diagnosing disorders [25].

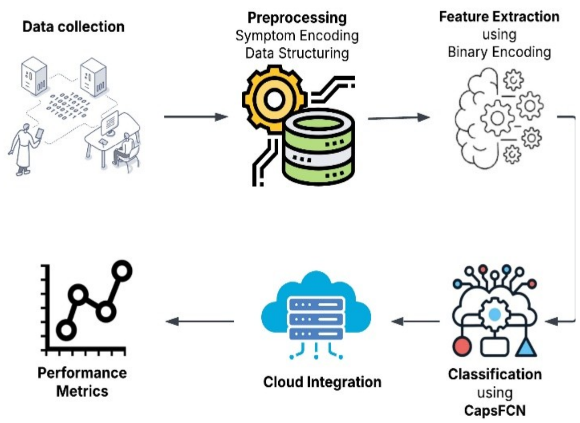

Figure 1 : CapsFCN Workflow for Mental Health Disorder Prediction

3.1 Data Collection:

Data collection thus proceeds with the first step in prediction modeling for mental health disorders through taking information from dependable and official sources, eg. clinical websites, medical journals, survey and diagnostic tools. This data mostly concerns mental health disorders and their respective associated symptoms. In essence, a thorough dataset is collected in terms of the presence or absence of specific symptoms, along with the corresponding mental health disorder for each case, so as to be able to derive the input data for the future processing (preprocessing), feature extraction, and training of the model-on every basis-from which a well-structured predictive model for mental health disorders could emerge [26].

3.2 Data Preprocessing

Data preprocessing in your case is, of course, proper usability for CapsFCN. The first part is symptom encoding: an encoding scheme in which each symptom receives a binary digit (0 or 1) that means absence and presence, respectively, for that symptom. A scalable Twofish encryption framework with preprocessing was developed for secure, efficient cloud storage of large financial datasets. Building on this, similar encryption and preprocessing techniques are applied to protect sensitive clinical mental health data, as illustrated by Bobba and Prema (2018) [27].This binary coding makes the data acceptable for modeling. Another task belonging to the data structure category is ensuring that the dataset has been properly structured with 24 Boolean columns, each denoting one of the symptoms, and one string column, denoting the corresponding mental health disorder. This is in a training-ready format. If any data entries are missing, they are appropriately imputed or rejected to have a clean dataset to carry competitive information onto feature extraction and model training.

3.2.1 Symptom Encoding:

In your work, symptoms are encoded by means of a binary value representation (0 or 1) to indicate their presence or absence in a given case. Symptoms are recorded for each single person, with 24 assigned symptoms; thus, if a symptom is found present, it is assigned a value of 1, while if absent, it is given a value of 0, resulting in the simplification of data that the model can absorb [28]. Mathematically, for a symptom S_i , with $i = 1,2,\dots,24$, we can express its encoding in eqn1:

$$S_i = \begin{cases} 1 & \text{if symptom } i \text{ is present} \\ 0 & \text{if symptom } i \text{ is absent} \end{cases} \quad \dots(1)$$

In effect, this transformation results in an individual feature vector comprised of 24 binary entries indicating the presence or absence of a particular symptom. These encoded values are then utilized as input features for the CapsFCN model in order to predict the respective mental health disorders.

3.2.2 Data Structuring:

You do work structuring the data-since the collected data are encoded into a structured format that can bear efficient loading by the model. The dataset consists of 24 different Boolean columns representing the symptoms, with each column representing a specific symptom and each row corresponding to an individual case assigned with respective symptoms [29]. The final column in the dataset holds the target variable -which is the associated mental health disorder for each case. Mathematically speaking, it would work in a way that for individual j, the dataset is represented as a vector of symptoms $\mathbf{S}_j$ and the corresponding mental health disorder D_j :

$$\mathbf{S}_j = [S_1, S_2, S_3, \ldots, S_{24}]$$
$$D_j = \text{Disorder}_j \qquad \ldots\ldots\ldots\ldots(2)$$

which states that $\mathbf{S}_j$ is the binary feature vector of symptoms for individual j , whereas D_j is the mental health disorder label (like Depression, Anxiety, etc.). With each row in the dataset corresponding to the specific individual with their symptoms and disorder label, it provides this structured input for the CapsFCN model to learn and make predictions.A cloud security framework using Multi-Factor Authentication, Attribute-Based Access Control, and AES encryption improves data confidentiality and reduces latency, as confirmed by Kethu (2018) [30]. This approach uplifts the proposed method's secure and efficient handling of mental health data in the cloud.

3.3 Feature Extraction

Feature extraction means that you convert the entered raw data, in particular binary-encoded symptoms, into meaningful features used in classification by your model. For this work, binary encoding is the main method of feature extraction, as all the 24 symptoms will be binary encoded: 0 or 1 for whether the symptoms are present or absent for a specific individual. These binary values thus generated form the feature set on which the CapsFCN model can learn how symptoms and mental health disorders interact [31]. The representation of the symptoms with structured binary data makes it possible to skip making complex feature extraction for the time being. The extracted feature set is fed directly to the hybrid CapsFCN model that makes use of encoded symptoms to classify accurately the mental health disorder.

3.3.1 Binary Encoding

Binary encoding in your task translates each symptom into binary, where '1' denotes presence and `0` indicates absence. This is an appropriate technique to transform qualitative symptom input into a quantitative portrayal for machine learning models like CapsFCN. For each case studied - there are 24 different symptoms and these are all assigned a binary value. This may be mathematically denoted as a vector S where for $i = 1,2,\ldots,24$, S is for a particular symptom and is defined in eqn3:

$$S_i = \begin{cases} 1 & \text{if symptom } i \text{ is present} \\ 0 & \text{if symptom } i \text{ is absent} \end{cases} \qquad \ldots.(3)$$

The feature vector $\mathbf{S}_j$ for instance j in eqn4:

$$\mathbf{S}_j = [S_1, S_2, S_3, \ldots, S_{24}] \qquad \ldots\ldots\ldots\ldots\ldots(4)$$

In this manner, the symptoms of each individual are encoded into a 24-dimensional vector of binary values, which will be provided as an input to the CapsFCN model to predict the corresponding mental health disorder.

3.4 Classification Using Capsnet

Figure 2 this is the CapsNet architecture diagram for processing and classifying symptom data. Input data contains an individual symptom encoded by a binary value (0 or 1). A 2D convolutional layer containing 32 filters and a 3x3 kernel serves as the first network step, extracting low-level features from input data followed by ReLU activation function to introduce non-linearity. Afterwards, max pooling (2x2) is implemented to down-sample the spatial dimension. The Primary Capsule Layer is designed to capture more complex patterns and interrelationships among symptoms, whereas Dynamic Routing helps capsules learn symbiotic hierarchical relationships from symptoms to disorders [32]. Finally, the Digit Capsule Layer (FC Layer) handles the output and predicts the associated mental health disorder. This CapsNet architecture allows for the learning of very complex relationships and dependencies among symptoms, thus enhancing the accuracy to predict mental health disorders with respect to the encoded symptom data.

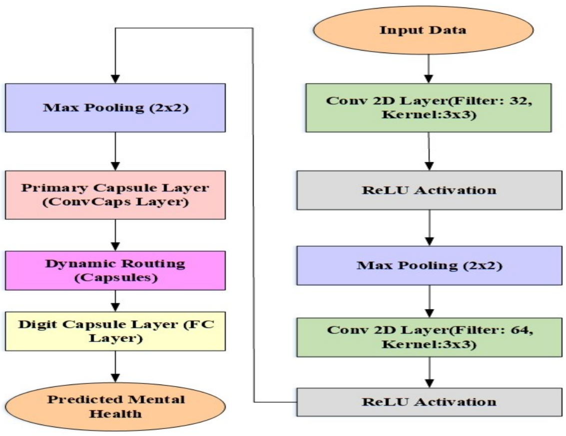

***Figure 2 :** CapsNet Architecture*

3.4.1 Conv 2D Layer:

This layer convolves the input data with 32 filters applying a 3x3 kernel. In mathematics, the convolution operation can be defined in eqn5:

$$\mathbf{X}_{\text{out}} = \mathbf{X}_{in} * \mathbf{W} + b \quad \text{..................(5)}$$

3.4.2 ReLU Activation:

An element-wise application of the Rectified Linear Unit (ReLU) activation function over the output of the convolution layer will convert it to nonlinearin eqn6:

$$\mathbf{ReLU}(x) = \max(0, x) \quad \text{..................(6)}$$

The activation function transforms all the negative values of feature map into 0 retaining only the positive values.

3.4.3 Max Pooling:

Max pooling is used to reduce the spatial dimensionality of the feature map, selecting from each of the 2x2 windows in feature map the highest valuein eqn7:

$$\mathbf{X}_{pool} = \max(\mathbf{X}_{in}) \quad \text{.......................(7)}$$

3.4.4 Primary Capsule Layer:

Capsule layers (groups of neurons) are used to ensure that spatial relations between properties are preserved. Each capsule learns the different characteristics of a feature such as whether a pattern is present or absent in it, by way of dynamic routing. Vasamsetty and Rathna (2018) [33] showed that combining LSTM's temporal modeling with Transformer's self-attention improves cloud threat detection. The offered solution extends this work by integrating hybrid models to enhance accuracy and adaptability in identifying cyber threats.In mathematical terms, the capsules transform the input vector into output vectors via some operations such in eqn8:

$$\mathbf{v}_j = \mathbf{Routing}(\mathbf{u}_j) \quad \text{.....................(8)}$$

3.4.5 Dynamic Routing:

The process ensures the dynamic connections of capsules given evidence that a feature exists. This dynamic routing mechanism updates the coefficients used for routing iteratively to determine a connection among capsules. This operation can be expressed in eqn9:

$$\mathbf{v}_j = \sum_i \square \, c_{ij}\mathbf{u}_i \quad \text{.....................(9)}$$

3.4.6 Digit Capsule Layer:

The digit capsule layer will show what the final classification brings forth concerning various state-of-mental disorders. The final output will pass through a fully connected layer (FC-layer) for a calculated prediction stage [34]. The last capsule output $\mathbf{v}_j$ will diagnose the mental health disorder at the moment of a SoftMax activation for probability computations in eqn10:

$$\hat{y}_j = \text{softmax}(\mathrm{v}_j) \quad \ldots\ldots\ldots\ldots\ldots\ldots..(10)$$

3.4 Cloud Integration

In our work, specifically cloud integration, we will deploy the trained CapsFCN model on a cloud-based platform to enhance scalability, accessibility, and resource efficiency. The model utilizes cloud infrastructure for processing large datasets, thus availing such services to health practitioners for predicting mental disorders [35].Continuous updating of the model as new data is generated is another advantage brought by cloud integration. More so, it provides secure storage of sensitive patient information while giving the computational power needed to run the model efficiently without dependence on local systems. With this approach, the model is flexible and accessible, providing a very effective solution for diagnosing mental conditions based on symptom data.

4. RESULT AND DISCUSSION

4.1 Performance Metrics

Figure 3labelled 'Performance Metrics' shows what could be a series of values and measures of accuracy obtained in considering a model's performance evaluation. Values are given expressed as percentages, with the lower bound being as low as 90%, possibly classified into various performance levels or thresholds. Expressed as 98.12% and 97.22% is the accuracy metric interpreted as precision for prediction by the model. The precision is also 97.57%, but with minimal attention to recall or F1-score, the usual metric for comparing between precision and recall in classification work. This diagram summarizes simple performance metrics-the measure of how the model is in terms of accuracy and precision. The computational framework draws on Jadon's (2018) [36] hybrid approach combining RFE, ELM, and SRC, which enhances feature selection, training speed, and accuracy to optimize performance by balancing precision and efficiency for AI applications.

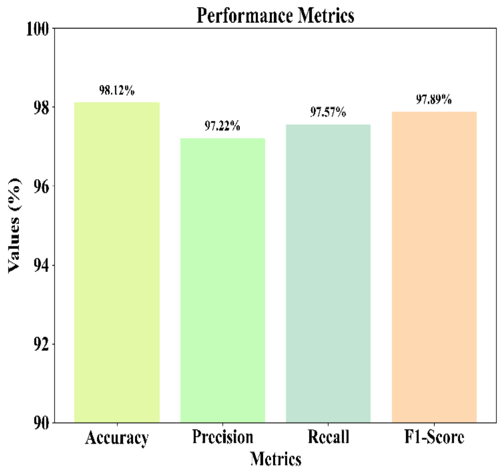

Figure 3: *Performance Metrics*

4.2 Latency vs Time for Cloud-Based Predictions

Cloud Based Prediction depicts the relationship between latency in milliseconds (ms) and time in seconds (s) to cloud-based prediction services [37]. Latency, defined on the y-axis, varies between 140 and 200 ms, while time, defined on the x-axis, is between 2 and 10 s. Likely, this graph provides insight into the performance and responsiveness of the cloud-based system under current conditions: how much the latency jumps or dips, as time goes on. Lower latency values would connote faster response time critical for the applications. This visualization enables understanding regarding a certain cloud service's stability and efficiency over a period of time, indicating possible delays or performance bottlenecks.

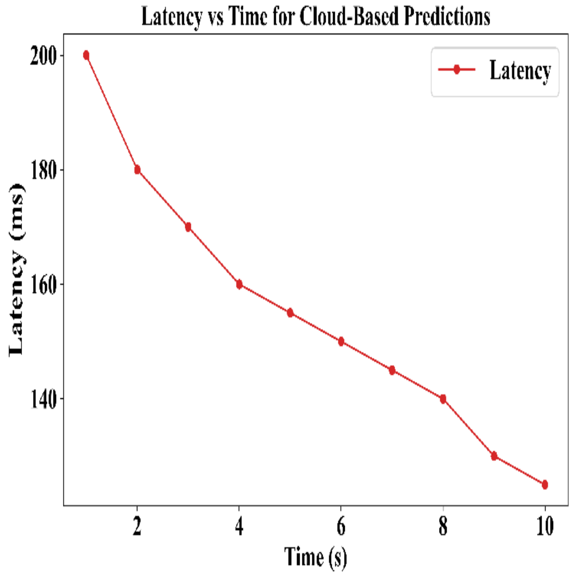

Figure 4 : *Latency vs Time for Cloud-Based Predictions*

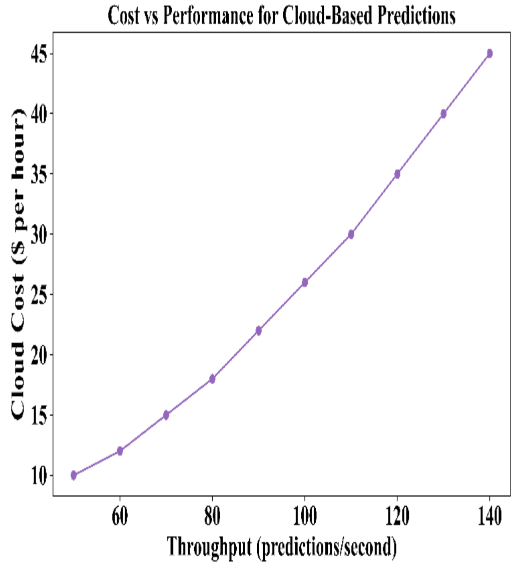

Figure 5 : *Cost vs Performance for Cloud-Based Predictions*

4.3 Cost vs Performance for Cloud-Based Predictions

Figure 5 seems to analyse the relationship between the cost of using the cloud and how well predictions are performed in a cloud-based setup. Such evaluation is done through two input parameters, namely “Cloud Cost (S per hour)” and “Time spent (predictions/second),” which shows that this chart analyses how the cost in terms of currency of cloud resources is related to the time derivative (speed) of predictions. This is a fundamental analysis in optimizing the allocation of cloud resources, as it indicates the least-cost arrangement that would still satisfy performance requirements. Balancing cost and performance will ensure that organizations can create a cheaper and more efficient system for cloud-based prediction [38].The conceptualized method integrates adaptive detection to optimize protection and efficiency against emerging quantum cyber threats, drawing upon lattice-based post-quantum cryptography’s strong security despite higher computational costs, as established by Garikipati and Palanisamy (2018).

5. CONCLUSION

In this article, we report the design and assessment of the CapsFCN model, a hybrid of Capsule Networks (CapsNet) and Fully Connected Neural Networks (FCNN), for the evaluation of mental disorders from clinical symptoms data. By virtue of integrating CapsNet, the model can capture the more complex spatial relations between symptoms, while the FCNN easily learns non-linear relationships in the dataset; this in itself leads to improved prediction outcomes. The addition of cloud computing further enables the model with better scalability and ease of accessibility, allowing health workers to make use of the system for timely diagnosis [40]. Evaluation of the proposed model was done using Accuracy, Precision, Recall, and F1 scores, which further substantiate that the model can reliably make clinical predictions. Thus, the results showed that CapsFCN could outperform the conventional diagnostic methods and give a more objective and consistent tool for clinical assessment on mental disorders. The future directions involve further development, improvement, testing with more datasets, and further optimizing the infrastructure of cloud computing for practical deployments into many health care setups.

REFERENCE:

[1] Wongkoblap, A., Vadillo, M. A., & Curcin, V. (2017). "Researching mental health disorders in the era of social media: systematic review". Journal of medical Internet research, 19(6), e228.

[2] Bernardini, F., Attademo, L., Cleary, S. D., Luther, C., Shim, R. S., Quartesan, R., & Compton, M. T. (2017). "Risk prediction models in psychiatry: toward a new frontier for the prevention of mental illnesses". The Journal of clinical psychiatry, 78(5), 18451.

[3] Mamidala, V., & Balachander, J. (2018). "AI-driven software-defined cloud computing: A reinforcement learning approach for autonomous resource management and optimization". International Journal of Engineering Research and Science & Technology, 14(3).

[4] Srividya, M., Mohanavalli, S., &Bhalaji, N. (2018). "Behavioral modeling for mental health using machine learning algorithms". Journal of medical systems, 42, 1-12.

[5] Bohon, L. M., Cotter, K. A., Kravitz, R. L., Cello Jr, P. C., & Fernandez y Garcia, E. (2016). "The theory of planned behavior as it predicts potential intention to seek mental health services for depression among college students". Journal of American college health, 64(8), 593-603.

[6] Richardson, T., Elliott, P., Roberts, R., & Jansen, M. (2017). "A longitudinal study of financial difficulties and mental health in a national sample of British undergraduate students". Community mental health journal, 53, 344-352.

[7] Cage, E., Di Monaco, J., & Newell, V. (2018). "Experiences of autism acceptance and mental health in autistic adults". Journal of autism and developmental disorders, 48, 473-484.

[8] Bakker, D., & Rickard, N. (2018). "Engagement in mobile phone app for self-monitoring of emotional wellbeing predicts changes in mental health: MoodPrism". Journal of affective disorders, 227, 432-442.

[9] Velten, J., Bieda, A., Scholten, S., Wannemüller, A., & Margraf, J. (2018). "Lifestyle choices and mental health: a longitudinal survey with German and Chinese students". BMC Public Health, 18, 1-15.

[10] Nagarajan, H., &Kurunthachalam, A. (2018). "Optimizing database management for big data in cloud environments". International Journal of Modern Electronics and Communication Engineering, 6(1).

[11] Richardson, T., Elliott, P., & Roberts, R. (2017). "Relationship between loneliness and mental health in students". Journal of public mental health, 16(2), 48-54.

[12] Levecque, K., Anseel, F., De Beuckelaer, A., Van der Heyden, J., & Gisle, L. (2017). Work organization and mental health problems in PhD students. Research policy, 46(4), 868-879.

[13] Lamond, J. E., Joseph, R. D., & Proverbs, D. G. (2015). "An exploration of factors affecting the long term psychological impact and deterioration of mental health in flooded households". Environmental research, 140, 325-334.

[14] Collishaw, S., Hammerton, G., Mahedy, L., Sellers, R., Owen, M. J.,

Craddock, N., & Thapar, A. (2016). "Mental health resilience in the adolescent offspring of parents with depression: a prospective longitudinal study". The Lancet Psychiatry, 3(1), 49-57.

[15] Husain, W., Xin, L. K., Rashid, N. A. A., & Jothi, N. (2016, August). "Predicting generalized anxiety disorder among women using random forest approach". In 2016 3rd international conference on computer and information sciences (ICCOINS) (pp. 37-42). IEEE.

[16] Garcia-Ceja, E., Riegler, M., Nordgreen, T., Jakobsen, P., Oedegaard, K. J., &Tørresen, J. (2018). "Mental health monitoring with multimodal sensing and machine learning: A survey". Pervasive and Mobile Computing, 51, 1-26.

[17] Gudivaka, R. K., & Rathna, S. (2018). "Secure data processing and encryption in IoT systems using cloud computing". International Journal of Engineering Research and Science & Technology, 14(1).

[18] Young, C. C., & Dietrich, M. S. (2015). "Stressful life events, worry, and rumination predict depressive and anxiety symptoms in young adolescents". Journal of Child and Adolescent Psychiatric Nursing, 28 (1), 35-42.

[19] Wang, J., Mann, F., Lloyd-Evans, B., Ma, R., & Johnson, S. (2018). "Associations between loneliness and perceived social support and outcomes of mental health problems: a systematic review". BMC psychiatry, 18, 1-16.

[20] Strohmeier, H., & Scholte, W. F. (2015). "Trauma-related mental health problems among national humanitarian staff: A systematic review of the literature". European journal of psychotraumatology, 6(1), 28541.

[21] Micali, N., Solmi, F., Horton, N. J., Crosby, R. D., Eddy, K. T., Calzo, J. P., & Field, A. E. (2015). "Adolescent eating disorders predict psychiatric, high-risk behaviors and weight outcomes in young adulthood". Journal of the American Academy of Child & Adolescent Psychiatry, 54(8), 652-659.

[22] Kessler, R. C., van Loo, H. M., Wardenaar, K. J., Bossarte, R. M., Brenner, L. A., Cai, T., & Zaslavsky, A. M. (2016). "Testing a machine-learning algorithm to predict the persistence and severity of major depressive disorder from baseline self -reports". Molecular psychiatry, 21 (10), 1366-1371.

[23] Chetlapalli, H., & Bharathidasan, S. (2018). "AI-based classification and detection of brain tumors in healthcare imaging data". International Journal of Life Sciences Biotechnology and Pharma Sciences, 14(2)

[24] Griffiths, S., Mond, J. M., Li, Z., Gunatilake, S., Murray, S. B., Sheffield, J., &Touyz, S. (2015). Self -stigma of seeking treatment and being male predict an increased likelihood of having an undiagnosed eating disorder. International Journal of Eating Disorders, 48(6), 775-778.

[25] Braithwaite, S., & Holt-Lunstad, J. (2017). "Romantic relationships and mental health". Current Opinion in Psychology, 13, 120-125.

[26] Alegría, M., NeMoyer, A., FalgàsBagué, I., Wang, Y., & Alvarez, K. (2018). "Social determinants of mental health: where we are and where we need to

go". Current psychiatry reports, 20, 1-13.

[27] Bobba, J., & Prema, R. (2018). "Secure financial data management using Twofish encryption and cloud storage solutions". International Journal of Computer Science Engineering Techniques, 3(4), 10–16.

[28] Shen, Y. C., Arkes, J., & Lester, P. B. (2017). "Association between baseline psychological attributes and mental health outcomes after soldiers returned from deployment". BMC psychology, 5, 1-12.

[29] Larson, S., Chapman, S., Spetz, J., & Brindis, C. D. (2017). "Chronic childhood trauma, mental health, academic achievement, and school-based health center mental health services". Journal of school health, 87 (9), 675-686.

[30] Kethu, S. S., & M, T. (2018). "Secure cloud-based CRM data management using AES encryption/decryption". International Journal of HRM and Organization Behavior, 6(3).

[31] Schroder, H. S., Dawood, S., Yalch, M. M., Donnellan, M. B., & Moser, J. S. (2015). "The role of implicit theories in mental health symptoms, emotion regulation, and hypothetical treatment choices in college students". Cognitive therapy and research, 39, 120-139.

[32] George, M. J., Russell, M. A., Piontak, J. R., & Odgers, C. L. (2018). "Concurrent and subsequent associations between daily digital technology use and high-risk adolescents' mental health symptoms". Child development, 89 (1), 78-88.

[33] Vasamsetty, C., & Rathna, S. (2018). "Securing digital frontiers: A hybrid LSTM-Transformer approach for AI-driven information security frameworks". International Journal of Information Technology and Computer Engineering, 6(1).

[34] Park, S., Lee, Y., Youn, T., Kim, B. S., Park, J. I., Kim, H., & Hong, J. P. (2018). "Association between level of suicide risk, characteristics of suicide attempts, and mental disorders among suicide attempters". BMC public health, 18, 1-7.

[35] Copeland, W. E., Bulik, C. M., Zucker, N., Wolke, D., Lereya, S. T., & Costello, E. J. (2015). "Does childhood bullying predict eating disorder symptoms? A prospective, longitudinal analysis". International journal of eating disorders, 48(8), 1141-1149.

[36] Jadon, R. (2018). "Optimized machine learning pipelines: Leveraging RFE, ELM, and SRC for advanced software development in AI applications". International Journal of Information Technology & Computer Engineering, 6(1).

[37] Allan, B. A., Dexter, C., Kinsey, R., & Parker, S. (2018). "Meaningful work and mental health: job satisfaction as a moderator". Journal of mental health, 27(1), 38-44.

[38] Cheng, H. L., Wang, C., McDermott, R. C., Kridel, M., & Rislin, J. L. (2018). Self-stigma, mental health literacy, and attitudes toward seeking psychological help. Journal of Counseling& Development, 96(1), 64 -74.

[39] Garikipati, V., & Palanisamy, P. (2018). "Quantum-resistant cyber defence in nation-state warfare: Mitigating threats with post-quantum cryptography". Indo-American Journal of Life Sciences and

Biotechnology, 15(3).

[40] Choi, K. W., Sikkema, K. J., Velloza, J., Marais, A., Jose, C., Stein, D. J., ... & Joska, J. A. (2015). "Maladaptive coping mediates the influence of childhood trauma on depression and PTSD among pregnant women in South Africa". *Archives of women's mental health*, *18*, 731-738.